IET Research Journals

IET Journals
The Institution of Engineering and Technology

Multi-nodal Short-term Energy Forecasting using Smart Meter Data

ISSN 1751-8644
doi: 0000000000
www.ietdl.org

B.P. Hayes[1], *J.K. Gruber*[2], *M. Prodanovic*[3]

[1] *Department of Electrical and Electronic Engineering, National University of Ireland Galway, University Road, Galway, Ireland*
[2] *MNI Technology on Wheels SL, Ronda de Poniente 12 - 2°, 28760 Tres Cantos, Madrid, Spain*
[3] *Electrical Systems Unit, IMDEA Energy Institute, Avda. Ramón de la Sagra, 3, 28935 Móstoles, Madrid, Spain*
** E-mail: barry.hayes@nuigalway.ie*

Abstract: This paper deals with the short-term forecasting of electrical energy demands at the local level, incorporating Advanced Metering Infrastructure (AMI), or "smart meter" data. It provides a study of the effects of aggregation on electrical energy demand modelling and multi-nodal demand forecasting. This paper then presents a detailed assessment of the variables which affect electrical energy demand, and how these effects vary at different levels of demand aggregation. Finally, the paper outlines an approach for incorporating AMI data in short-term forecasting at the local level, in order to improve forecasting accuracy for applications in distributed energy systems, microgrids and transactive energy. The analysis presented in the paper is carried out using large AMI data sets comprised of recorded demand and local weather data from test sites in two European countries.

1 Introduction

Short-Term Energy Forecasting (STEF) can be defined as the problem of forecasting energy demands over time periods from several hours to one week ahead. STEF is critical for the efficient operation of power and energy systems, particularly in the areas of energy balancing, energy market trading and management of system reserves [1, 2].

Recent developments in distributed energy systems, microgrids and transactive energy have led to new applications for STEF at a local, disaggregated level. A number of research works have investigated the forecasting of demand at each substation in the electricity network, or even at the individual feeder or end-user level [3–10].

The availability of Advanced Metering Infrastructure (AMI), or "smart meter" data provides much more detailed information on electricity end-use than was available in the past, greatly increasing the potential for accurate STEF at the local level. This paper deals with the application of AMI data in multi-nodal, localised demand forecasting. STEF is particularly challenging at the local level, since disaggregated demands are more volatile and noisy [10].

This paper presents several contributions in this area. First, this paper includes a study of the effects of aggregation on electrical energy demand modelling and multi-nodal demand forecasting. Second, it presents a detailed assessment of the variables which affect electrical energy demand, and how these effects vary at different levels of demand aggregation. Finally, it outlines an approach for incorporating AMI (or "smart meter") data in STEF at the local level, in order to provide more accurate STEF for applications in distributed energy systems, microgrids and transactive energy. The analysis presented in the paper is carried out using large AMI data sets comprised of recorded demand and local weather data from test sites in two European countries.

The paper is structured as follows: Section 2 discusses previous work and the current state of the art in this area. Section 3 provides a detailed assessment of the correlations between electrical energy demand and the variables which influence it, at each level of aggregation in the electricity network. Section 4 outlines the forecasting methods used, and Section 5 provides the results. Section 6 discusses the results and their implications and concludes the paper.

2 Literature Review

STEF approaches and techniques are very well-established, particularly for system-level applications in electricity market and transmission system operation. These forecasts typically focus on large-scale aggregated loads, such as electricity demands for entire countries or regions, or large network areas under Transmission System Operator (TSO) control. A range of different STEF approaches have been proposed in the literature, ranging from well-established regression methods [1], to approaches based on neural networks [11–13], to hybrid, or ensemble forecasting methods [14–16]. A summary of the current state of the art in STEF research can be found in [2, 17].

Recent work has examined the possibilities for improving system-level STEF by properly considering the demand and weather diversity across a large geographical area [18]. In [19], it was shown that local weather information can be exploited to improve system-level forecasts (i.e. using weather information from multiple weather stations improves results compared to a single average value.). A detailed study on combining point load forecasts is provided in [20]. Local demand correlations can potentially be exploited to improve the system level forecast, such as in [21], where this is achieved by clustering of residential users' smart meter data. Previous studies have also investigated pattern identification and clustering of smart meter data in order to classify user types and user behaviour (e.g. [22]), which can be useful for applications such as the design of demand response schemes.

At the electrcity distribution level, previous work has been carried out in the estimation of demands at the nodal or secondary substation level. Earlier work in this area investigated "load allocation", or the estimation of nodal demands through using the limited, low-resolution data available at the time, e.g. a combination of limited customer measurements, transformer peak load analysis and monthly billing data [23, 24]. The load allocation could also be carried out by applying user demand profile models, as in [25]. An Artificial Neural Network (ANN)-based model for distribution-level nodal demand forecasting was described in [26]. A method for time series STEF at distribution substations was discussed in [27] using information from individual large customers (which had detailed consumption measurement data) and customer load curves (for customers without detailed consumption measurements).

Distribution-level STEF has been carried out using more detailed disaggregated load data from SCADA or from smart metering systems in [3–10, 28–31]. In [29], the authors demonstrated an approach for multinodal forecasting in New Zealand distribution system using General Regression Neural Networks (GRNNs). In [30], the authors examine the impacts of user grouping on forecasting accuracy in the context of local electricity trading. A semi-parametric additive model for bus-level forecasting at around 2000 distribution substations automatically with highly-accurate results is demonstrated in [31]. In [32], each node in the distribution system is classified as a *regular* node or an *irregular* node. Nodes classified as irregular are forecasted by an individual forecasting model at each node.

Recently, applications in active distribution networks and microgrids have motivated research in STEF at the local level. These applications include: prediction of user load profiles for demand side management, e.g. [4, 5, 33]; energy storage optimisation (selection of optimal charge/discharge times and rates) [6]; electric vehicle integration [8]; and microgrid and virtual power plant applications [7, 34–36]. In addition, STEF at the local level can be used to provide load estimates for use in distribution system state estimation [9, 37].

In distribution-level STEF, a "top-down" approach has been widely used to forecast demand at multiple nodes. In the top-down approach, a forecast is made at the "parent" node (e.g. a primary distribution substation), and this is later allocated to the "child" nodes (e.g. the secondary substations connected downstream), using Load Distribution Factors (LDFs). The LDFs are calculated based on historical measurements or estimates of consumption at the child node. Alternatively, a "bottom-up" approach can be applied, where a forecast is made at each individual child node. The child node forecasts are then summed to provide the parent node forecast. With the widespread introduction of smart metering, much more detailed, localised information on electricity consumption is available, allowing for new possibilities for "bottom-up" forecasting approaches.

In the sections that follow in this paper, the "top-down" and "bottom-up" forecasting approaches are compared using two large smart meter data sets. The results in Section 5 indicate that a "bottom-up" approach incorporating smart meter data can give more accurate results than traditional "top-down" LDF-based forecasting, since LDF methods are based on the assumption that the demand pattern of each "child" node follows the demand pattern of its "parent" node. This assumption is often not valid at the distribution level, particularly if "smart grid" technologies such as electric vehicles, embedded generation, and energy storage are present in the demand. The following sections of the paper analyse the correlations between disaggregated demand and the variables which affect it, and discuss the effect of aggregation level on multi-nodal load forecasting.

3 Aggregation Effects on Energy Forecasting

The proliferation of AMI, or smart metering infrastructure, has led to the availability much more detailed, granular energy demand data for utilities, including energy demands at the individual user level. Energy demands at the lower levels of aggregation (e.g. individual user energy demand) are generally much more volatile than aggregated demands, where the averaging effect over a large number of users makes the demand time series less volatile and easier to forecast in the short-term.

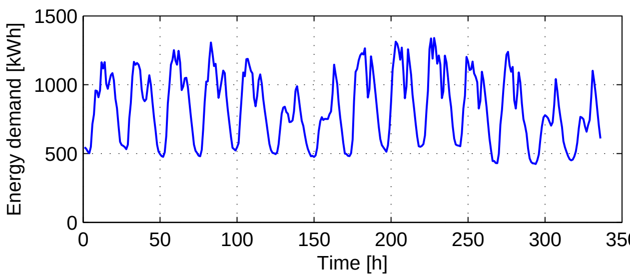

Fig. 1: Time series of aggregated energy demand for 1000 users.

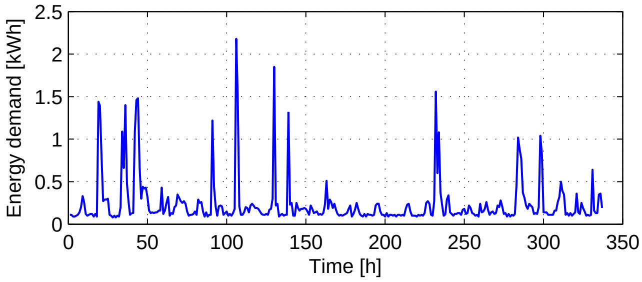

Fig. 2: Time series of energy demand for one individual user.

The concept of increasing demand volatility at lower aggregation levels is illustrated in Figs. 1 and 2. Figure 1 shows the aggregated energy demand for 1000 users over a period of around two weeks, indicating a clear day/night pattern and morning evening peaks in the time series. Figure 2 shows the energy demand for one randomly-selected individual user over the same two-week period. Here the time series is much more volatile with no clear daily pattern, and therefore it can be expected that it will be more difficult to predict this time series accurately.

Fig. 3 shows a sample of the day-ahead forecasting results from a linear autoregressive prediction model at various levels of demand aggregation, taken from previous work by the authors in [28]. It is clear that STEF accuracy decreases at low levels of aggregation. This is expected due to the higher volatility and variability of disaggregated loads. In the following sections of the paper, this "aggregation effect" is examined in detail.

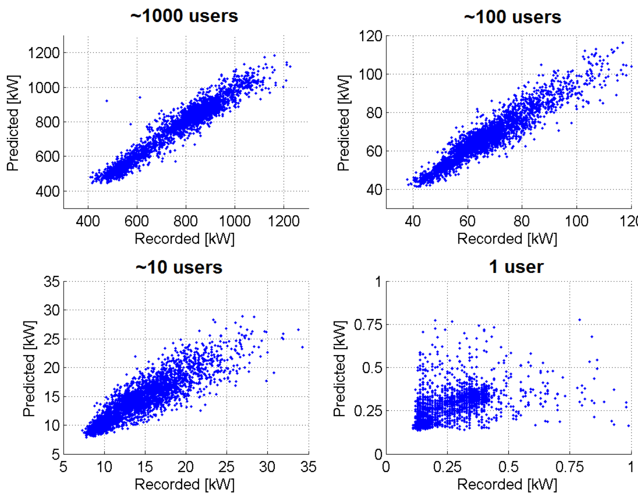

Fig. 3: Sample of results for day-ahead forecasting of hourly residential demand profiles at various levels of load aggregation [28].

3.1 Description of Data Sets

In this paper, two large data sets comprised of smart meter recordings were used. The first data set is taken from the EU project "SmartHG" [38]. Smart meter demand data was obtained from 1400 customers from a Danish distribution network operator for a continuous period of 24 months during 2012-2014, at a resolution of 1 hour. The corresponding local weather forecast data (including typical 24-hour ahead forecast errors) were obtained by request from the Danish Meteorological Institute [39].

The second data set is taken from the Irish Smart Metering Electricity Customer Behaviour Trials [40] which recorded half-hourly smart meter demand from 6500 customers over a period of 18 months at various distribution network locations in Ireland. Corresponding weather data was requested from the Irish Meteorological

Service [41]. In the paper, these data sets are subsequently referred to as the “Denmark" and “Ireland" data sets, respectively.

3.2 Selection of Predictor Variables

The variables which affect electrical energy demand in the short-term typically fall into three categories: time-related (e.g. day, hour of day, whether or not the day is a normal working day); historical (e.g. previous hour demand, previous week equivalent hour demand, previous 24 hour average); and weather-related (temperature has by far the greatest influence, but other weather factors such as humidity/precipitation, solar irradiation, and wind can also have effects). These correlation effects vary according to the level of aggregation of the energy demand.

In a multiple regression model the dependent variable is expressed as a function of several independent variables. The careful selection of the independent variables is an important issue and guarantees the quality of the model. Scatter and box plots can be used in a graphical analysis to gain insight into the relationship between dependent and independent variables.

Figure 4 shows the total aggregated demand in MW for all 1400 users in the Denmark data set. The demand is negatively correlated with the temperature and the dew point and positively correlated with the previous week equivalent hour demand, previous day equivalent hour demand and previous 24 hour average demand. In contrast, the relation between the load and the hour of day in Fig. 4 (b) does not show a clear linear correlation.

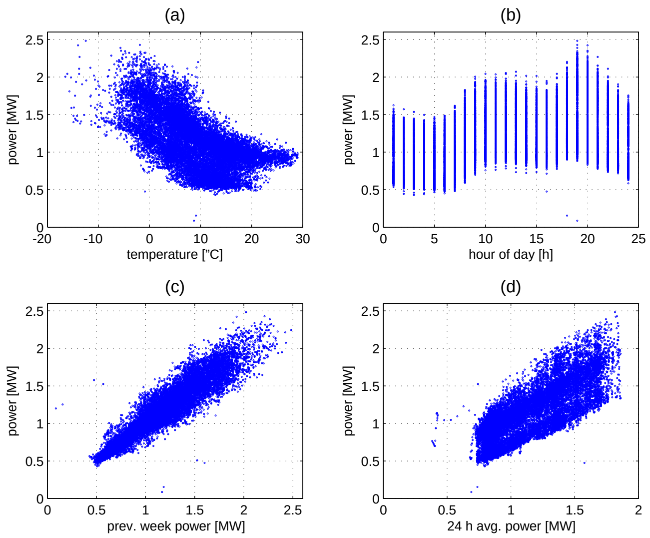

Fig. 4: Scatter plots of power demand (primary substation, Denmark) with respect to: (a) temperature, (b) hour of day, (c) previous week equivalent hour demand and (d) previous 24 hour average demand.

The graphical analysis suggests a linear relationship between demand and temperature, previous week equivalent hour demand, previous day equivalent hour demand, previous 24 hour average demand and working/non-working day condition*. Based on this graphical analysis, the independent variables, or “predictor variables" are selected for developing a linear demand forecasting model for examining the effects of aggregation in the analysis below.

More details on the relationship between the dependent and independent variables can be obtained with parametric regression techniques. These methods determine the unknown model parameters by minimizing some error index, usually the quadratic error between measured and predicted values of the dependent variable. The statistical significance of the obtained parameters can be tested using t-statistics or p-values.

For the Denmark and Ireland data sets, a linear model with an intercept (constant term) and eight regressors (independent variables) has been considered. The results showed that the intercept, temperature, hour of day, working/non-working day condition, previous week equivalent hour demand and previous day equivalent hour demand are significant at the 1% significance level ($|t| > 2.58$). In contrast, parameters related to the dew point, weekday and previous 24 hour average demand were less significant. The high value of the coefficient of determination ($R^2 = 0.958$) suggests a good fit of the model.

Another important issue in linear models is the problem of multicollinearity. Multicollinearity denotes the phenomenon when two or more predictor variables have a high degree of correlation. In both data sets used in this paper, a high correlation between the temperature and dew point regressors (correlation coefficient of 0.95) suggests that the temperature can be estimated from the dew point and vice versa. Furthermore, the previous 24 hour average demand can be predicted from the temperature and the previous day equivalent hour demand with a high degree of accuracy.

The information gathered in the previous analyses is used to select the most appropriate regressors. The graphical analysis and the t-statistic showed a negligible linear relationship between substation demand and weekday. In the case of the dew point and the previous 24 hour average demand, the graphical analysis reveals a clear linear relationship with the substation demand. The low significance of these regressors observed in the linear regression was a result of the detected multicollinearity. Based on the findings, the linear regression was repeated without the dew point, weekday and previous 24 hour average demand. The obtained t-statistics and p-values (see Table 1) underline the significance of the chosen independent variables. Furthermore, the coefficient of determination $R^2 = 0.958$ did not decrease with respect to the first regression.

The residuals of the linear regression, i.e. the difference between the measured and the estimated values, are frequently analysed for model validation. Different graphical and numerical methods can be used to check homoscedasticity, independence of residuals and other properties. A graphical analysis did not show any significant correlation between the residuals from the regression for the Denmark data set and the independent variables (see Fig. 5 for an example).

Table 1 Results of the linear regression.

Variable	Estimate	t-statistic	p-value
Intercept	$7.30 \cdot 10^{-2}$	23.33	$1.25 \cdot 10^{-118}$
Temperature	$-3.66 \cdot 10^{-3}$	-33.23	$6.02 \cdot 10^{-235}$
Hour of day	$1.87 \cdot 10^{-3}$	18.74	$1.39 \cdot 10^{-77}$
Working day	$2.75 \cdot 10^{-2}$	22.81	$1.58 \cdot 10^{-113}$
Prev. week	$2.18 \cdot 10^{-1}$	48.01	0
Prev. day	$7.11 \cdot 10^{-1}$	148.19	0

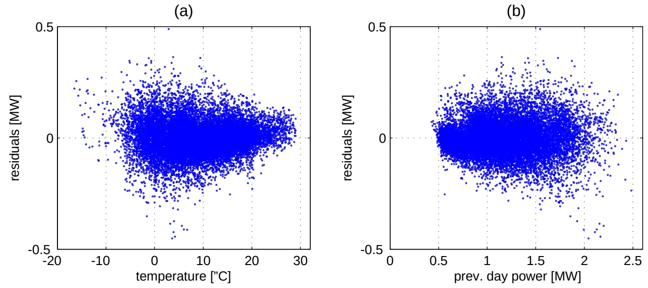

Fig. 5: Scatter plots of the residuals from linear regression with respect to: (a) temperature and (b) previous day equivalent hour demand.

The model distinguishes between working and non-working days, but it does not specifically account for public holidays or other special events. In practice, the STEF model prediction accuracy may be slightly reduced during public holidays and other days with special events.

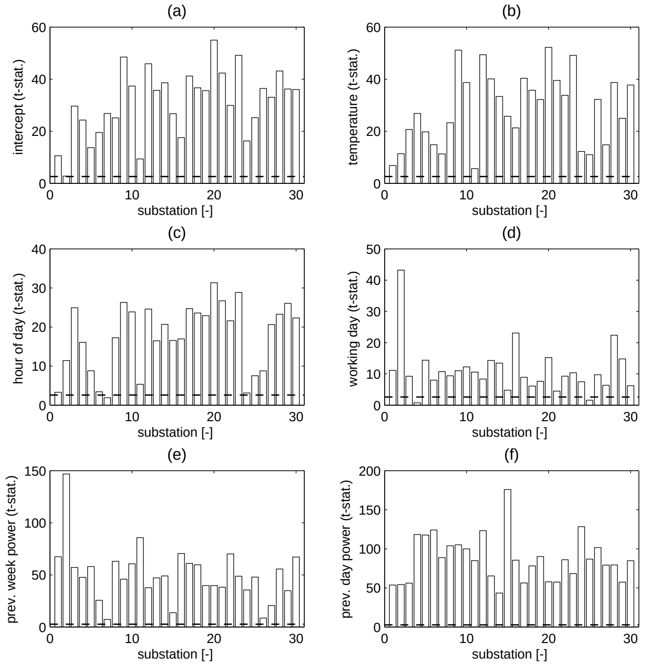

Fig. 6: T-statistics (bars) and 1 % significance level (dashed lines) for linear model parameters (Danish secondary substations): (a) intercept, (b) temperature, (c) hour of day, (d) working/non-working day, (e) previous week equivalent hour demand and (f) previous day equivalent hour demand.

The multiple regression was repeated for each of the 30 secondary electricity distribution substations in the geographic area of the Denmark data set. The number of users at each substation varied, with an average of 47 individual users connected downstream. The detailed analysis showed a strong linear relationship between the secondary substation demand (predictor variable) and temperature, hour of day, working/non-working day condition, previous week equivalent hour demand and previous day equivalent hour demand (dependent variables). It was proven that the estimated model parameters (intercept and five regressors) are significant at the 1% significance level for almost all secondary substations (see Fig. 6). For the secondary substation models the obtained average coefficient of determination is $R^2 = 0.748$.

3.3 Aggregation Effects on Demand Modelling and Forecasting

In this section, the influence of the aggregation effect on energy forecasting is examined using multiple linear regression. Multiple linear regression models are very well-established and widely used for STEF [1]. The general model can be expressed as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_k x_{ik} + e_i \qquad (1)$$

where the y represents the deviation of observed values from the mean demand value μ_y. The predictor variables (e.g. temperature, previous week demand, previous day demand) are represented by $x_1, x_2, ..., x_k$, and the coefficients for the predictor variables are $\beta_1, \beta_2, ..., \beta_k$. The intercept is represented by β_0 and e is the model error for observations $i = 1, 2, ..., N$.

The model parameters $b_0, b_1, b_2, ..., b_k$ are calculated by fitting a sample of the data by a least-squares error minimisation. The sample regression model can be expressed as:

$$y_i = b_0 + \sum_{i=1}^{k} b_i x_{ik} + e_i \qquad (2)$$

where b_k is the sample estimate of β_k. The coefficient of determination R^2 is given by:

$$R^2 = \frac{\sum_{i=1}^{N}(\hat{y}_i - \bar{y})}{\sum_{i=1}^{N}(y_i - \bar{y})} \qquad (3)$$

R^2 is a measure of the amount of variability in y that is explained by the x variables in the model, and is used here an indicator of the "fit" of the linear prediction model.

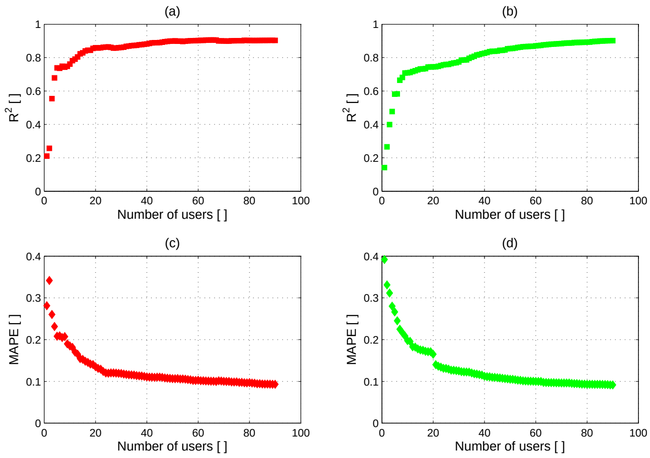

Fig. 7: Effect of aggregation on coefficient of determination R^2 and 24 hour ahead prediction error: (a) R^2 for 1-90 users, Denmark data set; (b) R^2 for 1-90 users, Ireland data set; (c) MAPE for 1-90 users, Denmark data set; (d) MAPE for for 1-90 users, Ireland data set.

Figure 7 shows the changes in R^2 and in the 24 hour ahead prediction error for 1-90 users in both data sets, using the multiple linear regression model. The prediction error is expressed as the Mean Absolute Percentage Error (MAPE). It is shown in Figure 7 that R^2 increases almost exponentially as more users are aggregated together, indicating that the model fit improves as more users are aggregated together. There is a corresponding exponential decrease in the prediction error (MAPE). Similar results were obtained for both the Denmark and Ireland data sets.

Figure 8 shows the R^2 prediction error in MAPE, for a larger number of users (1-1400 users from the Ireland data set). Again R^2 increases exponentially until it converges on a value of approximately $R^2 = 0.96$ at around 200 users. The prediction error decreases exponentially until it reaches a MAPE of 5-6% with 1000 users.

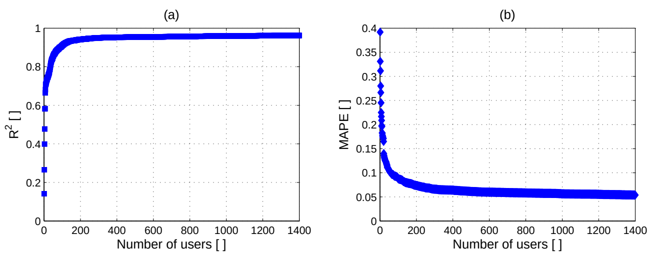

Fig. 8: Effect of aggregation on coefficient of determination R^2 and 24 hour ahead prediction error with larger number of users: (a) R^2 for 1-1400 users, (b) MAPE for 1-1400 users.

The above multiple regression analysis provides insight into the effect of aggregation on modelling fit and prediction accuracy. This analysis allows us to determine what level of forecasting accuracy can be expected at each level of aggregation, for example, 20 users aggregated together is likely to result in an R^2 value of 0.85 and a 24 hour ahead forecasting error in the range of 15%, while 50 users aggregated together can be expected to give $R^2 > 0.9$ and MAPE of

10%. The analysis above also illustrates the difficulty in forecasting with small numbers of individual users. When the number of users is less than 10, model fitting is problematic with $R^2 < 0.8$ and large forecasting errors (MAPE > 20%).

4 Multi-nodal Demand Forecasting

This section outlines the forecasting methodology used in the paper for forecasting demand at multiple nodes in a distribution network. It compares the traditional Top-Down (TU) forecasting approach and the proposed Bottom-Up (BU) approach using smart meter data. Figure 9 shows an example of recorded demands at a "parent" node (e.g. at a distribution network substation), and the corresponding "child" nodes downstream (e.g. the individual distribution feeders), over a period of one week.

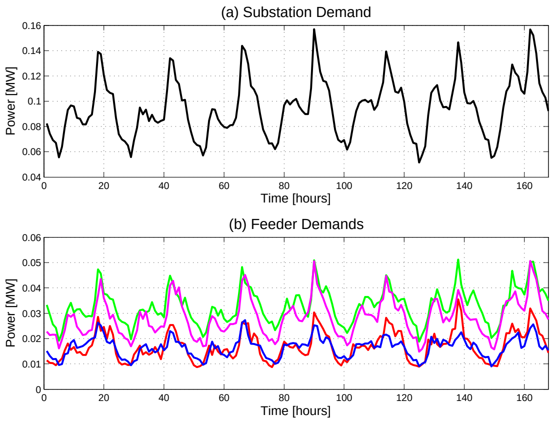

Fig. 9: Example of recorded demands at "parent" node and "child" nodes downstream.

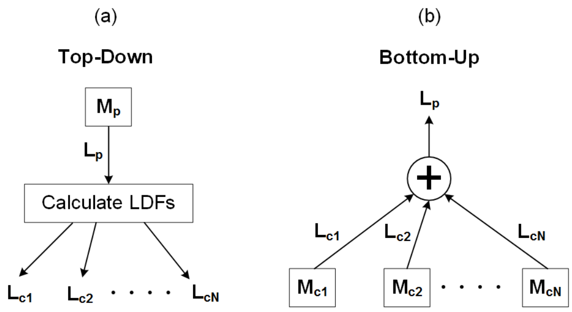

Fig. 10: Load forecasting: (a) Top-Down (TD) approach and (b) Bottom-Up (BU) approach.

The TD and BU approaches to load forecasting are illustrated graphically in Figure 10. In the TD approach, the load forecast L_p at the "parent" node (e.g. the substation) is made using the model M_P. The parent node forecast is then allocated, or divided, proportionately among the "child" nodes downstream (e.g. the distribution feeders), using Load Distribution Factors (LDFs).

4.1 "Top-Down" and "Bottom-Up" Forecasting Approaches

Load Distribution Factors (LDFs) are widely used for top-down load forecasting at the distribution level, in order to allocate parent load forecast proportionately among the child nodes downstream. This is based on the principle that the load pattern of the child node follows that of the parent node. The LDFs used in this paper were calculated using the method outlined in [32]. In order to forecast the load of node i on day k, LDFs are estimated by the averaged LDFs of the past S weeks having the same day of the week index. This is expressed mathematically as:

$$LDF(i,k,t) = \frac{1}{S}\sum_{s=1}^{S}\frac{L_c(i,k-7s,t)}{L_p(k-7s,t)} \tag{4}$$

where: s represents the day of the week index, t represents the time (expressed in this paper in hours), $L_c(i,k,t)$ is the child node forecast and $L_p(k,t)$ is the parent node load forecast.

The forecast for child node i is then given by:

$$\hat{L_c}(i,k,t) = \hat{L_p}(k,t) * LDF(i,k,t) \tag{5}$$

In the BU approach, forecasts are made at each child node $L_{c1}, L_{c2}, ..., L_{cN}$ using individual node forecasting models $M_{c1}, M_{c2}, ..., M_{cN}$. These can then be combined to create the forecast at the parent node:

$$\hat{L_p}(k,t) = \sum_{i=1}^{N}\hat{L_c}(i,k,t) \tag{6}$$

5 Multi-nodal Forecasting Results

This section provides results of STEF applied at multiple nodes in an electricity distribution network, and compares the TD and BU approaches using smart meter data aggregated at the secondary substation level. STEF at this level of aggregation is becoming increasingly important for applications in distributed grid operation, microgrids, and transactive energy. The Denmark data set is used for the analysis in this section, since the geographical location and the network node each individual user is connected to is known*.

The multiple linear regression described in (1)-(2), Section 3.2 is applied to carry out STEF at each node. The Denmark data set was split in a 50:50 ratio into "model training" data and "model validation" data, resulting in 12 months of training data and 12 months of validation data. The forecasting model was specified and trained using the training data only, and all forecasting results shown are calculated using the validation data only.

There are 30 secondary electricity distribution substations, or network nodes, in the geographic area of the Denmark data set, where each node had an average of 47 individual users connected downstream. The electricity demand at each of these nodes is made up mainly of residential electricity consumption. The corresponding forecasting results for both the TD and BU approaches are shown in Section 5.1.

In order to consider a future scenario with significant numbers of Electric Vehicles (EVs) embedded at the residential level, EV charging load is added to this residential demand. The added EV charging loads are taken from actual vehicle charging data from the Test-an-EV project in [42]. The EVs considered in the analysis have 16 kWh battery capacity and 13 kW power rating. In the analysis in Section 5.2, EV charging loads are added to a percentage of randomly-selected households in the residential demand data set.

5.1 Multi-nodal Forecasting of Electricity Demands

A summary of the results obtained at multiple nodes in the electricity distribution network is shown in Figs. 11-13. At the secondary substation level, it was observed that better forecasting accuracy was obtained using the BU approach.

The error statistics for the TD and BU approaches are given in Table 2. The results show that the BU forecasting approach provided a 8.5% improvement in the mean error and a 23.6% improvement in

For the Ireland data set, the smart meter data are randomised and the network locations are unknown, and therefore it is not possible to assign individual users to the correct node.

the standard deviation of the error compared to the TD approach. The bias error is defined as the mean or expected value of the forecasting error. The TD and BU forecasts are considered unbiased since the bias errors are very small in both cases ($< 0.02\%$).

In order to determine if the difference in errors between the TD and BU forecasting approaches was significant, a two-sample t-test was carried out. It was found that the improvement in forecasting error using the BU approach was statistically significant at 21 of the 30 secondary substation nodes tested, with a mean t-statistic of 6.4 across the 30 nodes. The significance level considered was 5%.

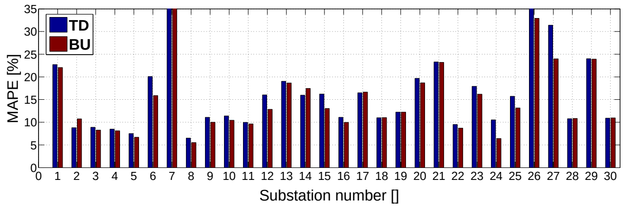

Fig. 11: Summary of 24 hour ahead forecasting errors at secondary substations: average MAPE values.

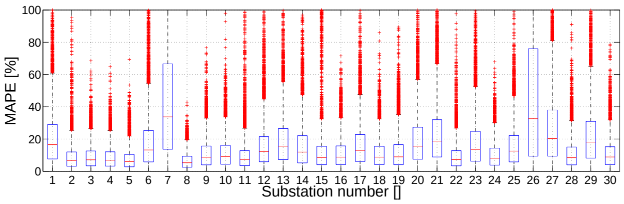

Fig. 12: Summary of 24 hour ahead forecasting errors at secondary substations: TD approach boxplots.

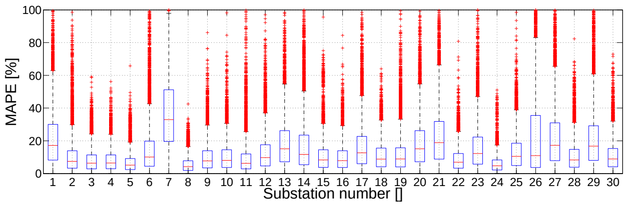

Fig. 13: Summary of 24 hour ahead forecasting errors at secondary substations: BU approach boxplots.

Table 2 Summary of error statistics for TD and BU approaches at 30 nodes.

	Average MAPE [%]	Std. dev. MAPE [%]	Bias Error [%]
TD	10.78	7.03	0.0044
BU	9.87	5.37	0.0160

5.2 *Multi-nodal Forecasting with Embedded Electric Vehicle Load*

In this section, the same forecasting analysis using the TD and BU approaches is carried out, for EV penetrations of 10% and 20%, using actual EV charging data from the "Test-an-EV" project [42]. The results for 10% EV penetration are summarised in Fig. 14 and

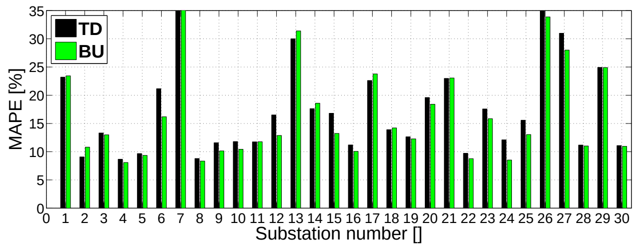

Fig. 14: Summary of 24 hour ahead forecasting errors at secondary substations with 10% EV penetration.

Table 3 Summary of error statistics with 10% EV penetration.

	Average MAPE [%]	Std. dev. MAPE [%]	Bias Error [%]
TD	11.22	7.75	0.0125
BU	10.23	5.94	0.0176

Table 3. The BU forecasting approach provided a 8.8% improvement in the mean error and a 23.3% improvement in the standard deviation of the error compared to the TD approach. It was found using the two-sample t-test that the improvement in forecasting error using the BU approach was statistically significant at 21 of the 30 secondary substation nodes.

Finally, the results for 20% EV penetration are given in Fig. 15 and Table 4, where BU forecasting approach provided a 8.6% improvement in the mean error and a 22.9% improvement in the standard deviation of the error compared to TD. The improvement in forecasting error using the BU approach was statistically significant at 20 of the 30 secondary substation nodes.

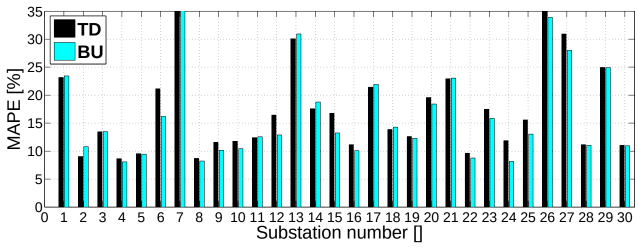

Fig. 15: Summary of 24 hour ahead forecasting errors at secondary substations with 20% EV penetration.

Table 4 Summary of error statistics with 20% EV penetration.

	Average MAPE [%]	Std. dev. MAPE [%]	Bias Error [%]
TD	11.26	7.68	0.0076
BU	10.29	5.92	0.0170

5.3 *Computational Requirements*

The BU approach requires more computational effort than TD, since more individual forecasts need to be made; the BU approach requires forecasting at all child nodes, while TD only requires a forecast to be made at the parent node. In order to calculate the results shown in Figs. 11-15, with one parent node and 30 child nodes, each daily load profile forecast required 0.014s using the TD approach, and

0.083s using the BU approach*. The computational effort for the BU approach increases linearly with the number of child nodes.

6 Conclusions

This paper discusses the application of AMI, or “smart meter" data to multi-nodal short-term energy forecasting at the distribution network level. In the first part of the analysis, the aggregation effect is examined in detail using multiple linear regression. It was shown using large AMI data sets from two European countries that model fit and prediction accuracy are highly dependent on the number of individual users aggregated together.

These results have important implications for applications such as transactive energy and microgrids, since they clearly illustrate the limitations of standard forecasting models when applied to smaller groups of users. Specifically, the results in Section 3 demonstrate the difficulty in achieving an acceptable model fit and prediction accuracy (e.g. $R^2 > 0.8$ and day ahead forecasting MAPE $< 10\%$) for groups of less than 20 users using a standard linear prediction model. This analysis can be used to better quantify the model fitting for varying numbers of users, and to select the appropriate aggregation level for energy forecasting using AMI data.

The results in Section 5 demonstrate the advantages of a “bottom-up" forecasting approach compared to the traditional “top-down approach used for load forecasting, which applies Load Distribution Factors (LDFs). The key point is that traditional LDF-based forecasting is based on the idea that the demand pattern of each “child" node (e.g. a secondary substation) generally follows the demand pattern of its “parent" node (e.g. a primary substation). However, this assumption is not valid at the distribution level, particularly if smart grid technologies such as EVs are present in the demand.

If applied correctly, a “bottom-up" forecasting approach using smart metering data gives better results. Overall the results showed better performance for the “bottom-up" approach in all cases analysed in the paper. The bottom-up approach requires more computational effort due to fact that each node needs to be forecasted individually. However, the presented linear prediction model is fast enough that this extra computational burden is not expected to be a major concern (e.g. several seconds for day-ahead forecasting of 1000s of nodes).

There was some slight seasonal variation in both the TD and BU model performance, with lower errors occurring in winter and spring (8-9% average MAPE) and higher errors occurring in summer and autumn (9-10% average MAPE). For simplicity, only one prediction model to cover all of the seasons was considered in this paper. It may be possible to gain improvements in the model prediction accuracy by developing seasonal multiple linear regression models, at the expense of increased complexity and modelling effort.

Future work will investigate the incorporation of smart meter data in multi-nodal STEF with more advanced forecasting methods than the simple multiple linear regression model used in this paper. This will include the application of artificial intelligence-based methods to estimate the STEF model parameters. In addition to this, the use of machine learning tools such as neural networks for forecasting multi-nodal demands will be examined.

Acknowledgment

The authors kindly acknowledge the support of the European Commission provided through the Marie Curie researcher mobility action (FP7-PEOPLE-2013-COFUND), and the SmartHG research project (FP7-ICT-2011-8).

All calculations were carried out using MatLab on a standard PC with a 2.3 GHz processor and 8GB RAM

References

7 References

1 G. Gross and F.D. Galiana. Short-term load forecasting. *Proceedings of the IEEE*, 75(12):1558–1573, Dec 1987.
2 Tao Hong. *Short Term Electric Load Forecasting*. PhD thesis, North Carolina State University, 2010.
3 B. Hayes, I. Hernando-Gil, A. Collin, G. Harrison, and S. Djokić. Optimal power flow for maximizing network benefits from demand-side management. *IEEE Transactions on Power Systems*, 29(4):1739–1747, 2014.
4 B. Moradzadeh and K. Tomsovic. Two-stage residential energy management considering network operational constraints. *IEEE Transactions on Smart Grid*, 4(4):2339–2346, Dec 2013.
5 A. Molderink, V. Bakker, M.G.C. Bosman, J.L. Hurink, and G.J.M. Smit. Management and control of domestic smart grid technology. *IEEE Transactions on Smart Grid*, 1(2):109–119, Sept 2010.
6 M. Rowe, T. Yunusov, S. Haben, C. Singleton, W. Holderbaum, and B. Potter. A peak reduction scheduling algorithm for storage devices on the low voltage network. *IEEE Transactions on Smart Grid*, 5(4):2115–2124, July 2014.
7 A. Mohamed, V. Salehi, and O. Mohammed. Real-time energy management algorithm for mitigation of pulse loads in hybrid microgrids. *IEEE Transactions on Smart Grid*, 3(4):1911–1922, Dec 2012.
8 A. Mohamed, V. Salehi, Tan Ma, and O. Mohammed. Real-time energy management algorithm for plug-in hybrid electric vehicle charging parks involving sustainable energy. *IEEE Transactions on Sust. Energy*, 5(2):577–586, April 2014.
9 B. P. Hayes, J. K. Gruber, and M. Prodanovic. A closed-loop state estimation tool for mv network monitoring and operation. *IEEE Transactions on Smart Grid*, 6(4):2116–2125, July 2015.
10 Stephen Haben, Jonathan Ward, Danica Vukadinovic Greetham, Colin Singleton, and Peter Grindrodoad. A new error measure for forecasts of household-level, high resolution electrical energy consumption. *International Journal of Forecasting*, 30(2):246 – 256, 2014.
11 H.S. Hippert, C.E. Pedreira, and R.C. Souza. Neural networks for short-term load forecasting: a review and evaluation. *IEEE Transactions on Power Systems*, 16(1):44–55, Feb 2001.
12 Ali Deihimi, Omid Orang, and Hemen Showkati. Short-term electric load and temperature forecasting using wavelet echo state networks with neural reconstruction. *Energy*, 57:382 – 401, 2013.
13 Chia-Nan Ko and Cheng-Ming Lee. Short-term load forecasting using svr (support vector regression)-based radial basis function neural network with dual extended kalman filter. *Energy*, 49:413 – 422, 2013.
14 JinXing Che and JianZhou Wang. Short-term load forecasting using a kernel-based support vector regression combination model. *Applied Energy*, 132:602 – 609, 2014.
15 Song Li, Lalit Goel, and Peng Wang. An ensemble approach for short-term load forecasting by extreme learning machine. *Applied Energy*, 170:22 – 29, 2016.
16 M. Ghofrani, M. Ghayekhloo, A. Arabali, and A. Ghayekhloo. A hybrid short-term load forecasting with a new input selection framework. *Energy*, 81:777 – 786, 2015.
17 Tao Hong and Shu Fan. Probabilistic electric load forecasting: A tutorial review. *International Journal of Forecasting*, 32(3):914 – 938, 2016.
18 Shu Fan, K. Methaprayoon, and Wei-Jen Lee. Multiregion load forecasting for system with large geographical area. *IEEE Transactions on Industry Applications*, 45(4):1452–1459, July 2009.
19 Shu Fan, Luonan Chen, and Wei-Jen Lee. Short-term load forecasting using comprehensive combination based on multimeteorological information. *IEEE Transactions on Industry Applications*, 45(4):1460–1466, July 2009.
20 Jakub Nowotarski, Bidong Liu, Rafal Weron, and Tao Hong. Improving short term load forecast accuracy via combining sister forecasts. *Energy*, 98:40 – 49, 2016.
21 F.L. Quilumba, Wei-Jen Lee, Heng Huang, D.Y. Wang, and R.L. Szabados. Using smart meter data to improve the accuracy of intraday load forecasting considering customer behavior similarities. *Smart Grid, IEEE Transactions on*, 6(2):911–918, March 2015.
22 S. Haben, C. Singleton, and P.glet Grindrod. Analysis and clustering of residential customers energy behavioral demand using smart meter data. *IEEE Transactions on Smart Grid*, 7(1):136–144, Jan 2016.
23 V. Miranda, J. Pereira, and J.T. Saraiva. Load allocation in dms with a fuzzy state estimator. *IEEE Transactions on Power Systems*, 15(2):529–534, May 2000.
24 Jie Wan and K.N. Miu. Weighted least squares methods for load estimation in distribution networks. *IEEE Transactions on Power Systems*, 18(4):1338–1345, Nov 2003.
25 R.P. Broadwater, A.H. Khan, H.E. Shaalan, and R.E. Lee. Time varying load analysis to reduce distribution losses through reconfiguration. *IEEE Transactions on Power Delivery*, 8(1):294–300, Jan 1993.
26 S.A. Villalba and C.A. Bel. Hybrid demand model for load estimation and short term load forecasting in distribution electric systems. *IEEE Transactions on Power Delivery*, 15(2):764–769, Apr 2000.
27 Haibin Wang and Noel Schulz. Using AMR data for load estimation for distribution system analysis. *Electric Power Systems Research*, 76(5):336 – 342, 2006.
28 B. P. Hayes, J. K. Gruber, and M. Prodanovic. Short-term load forecasting at the local level using smart meter data. In *PowerTech, 2015 IEEE Eindhoven*, pages 1–6, June 2015.
29 K. Nose-Filho, A.D.P. Lotufo, and C.R. Minussi. Short-term multinodal load forecasting using a modified general regression neural network. *IEEE Transactions on Power Delivery*, 26(4):2862–2869, Oct 2011.
30 P. Goncalves Da Silva, D. Ilic, and S.cal Karnouskos. The impact of smart grid prosumer grouping on forecasting accuracy and its benefits for local electricity

market trading. *IEEE Transactions on Smart Grid*, 5(1):402–410, Jan 2014.
31 Y. Goude, R. Nedellec, and N. Kong. Local short and middle term electricity load forecasting with semi-parametric additive models. *IEEE Transactions on Smart Grid*, 5(1):440–446, Jan 2014.
32 X. Sun, P. B. Luh, K. W. Cheung, W. Guan, L. D. Michel, S. S. Venkata, and M. T. Miller. An efficient approach to short-term load forecasting at the distribution level. *IEEE Transactions on Power Systems*, 31(4):2526–2537, July 2016.
33 S. Paoletti, M. Casini, A. Giannitrapani, A. Facchini, A. Garulli, and A. Vicino. Load forecasting for active distribution networks. In *IEEE PES Innovative Smart Grid Technologies (ISGT Europe)*, pages 1–6, Dec 2011.
34 L. Hernandez, C. Baladron, J.M. Aguiar, B. Carro, A. Sanchez-Esguevillas, J. Lloret, D. Chinarro, J.J. Gomez-Sanz, and D. Cook. A multi-agent system architecture for smart grid management and forecasting of energy demand in virtual power plants. *IEEE Commucations Magazine*, 51(1):106–113, January 2013.
35 Luis Hernandez, Carlos Baladron, Javier M. Aguiar, Belen Carro, Antonio Sanchez-Esguevillas, and Jaime Lloret. Artificial neural networks for short-term load forecasting in microgrids environment. *Energy*, 75:252 – 264, 2014.
36 Nian Liu, Qingfeng Tang, Jianhua Zhang, Wei Fan, and Jie Liu. A hybrid forecasting model with parameter optimization for short-term load forecasting of micro-grids. *Applied Energy*, 129:336 – 345, 2014.
37 B.P. Hayes and M. Prodanovic. State forecasting and operational planning for distribution network energy management systems. *IEEE Transactions on Smart Grid*, 7(2):1002–1011, 2016.
38 European Commision SmartHG project website: http://www.smarthg.eu/, accessed 3 March 2018.
39 Danish Meteorological Institute: http://www.dmi.dk/en/vejr/, accessed 3 March 2018.
40 CER Smart Metering Project website: http://www.ucd.ie/issda/data/, accessed 3 March 2018.
41 Met Éireann (Irish Meteorological Service): http://www.met.ie, accessed 3 March 2018.
42 Test-an-EV project. Electrical Vehicle (EV) Data: http://smarthg.di.uniroma1.it/test-an-ev/, accessed 3 March 2018.